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SHORT-TERM LOAD FORECASTING IN SMART GRIDS USING MACHINE LEARNING: A COMPARATIVE ANALYSIS OF REGRESSION-BASED MODELS

Muhammad Zafir Bin Zia[*1], Raja Muhammad Ahmad Khan Janjua[2], Muhammad Talha Yasir[3], Muhammad Hasnain Ali[4] , Hassan Masood[5], Hashir Sarfraz Malik[6]

[*1,2,3,4,5,6]*Department of Electrical Engineering, MCS, National University of Sciences and Technology (NUST)*

[*1] muhammadzafir248@gmail.com , [2]rajamakj@gmail.com , [3]mtalhayasir210@gmail.com , [4]muhammadhasnainali0320@gmail.com , [5]hassanmasood471@gmail.com, [6]hashirsarfrazmalik@gmail.com

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Corresponding Author: * Muhammad Zafir Bin Zia

Abstract
Precise short-term load forecasting (STLF) is vital for the better efficiency, reliability, and sustainability of contemporary smart grids. With the rising deployment of smart meters and advanced metering infrastructure, there are ample amounts of high-resolution electricity consumption data available, which has paved the way for the use of machine learning (ML) methods for enhanced demand forecasting. The paper offers a comparative study of three regression-driven ML algorithms, Linear Regression, Decision Tree Regressor and Random Forest. Used for predicting hourly electricity load. The models are implemented and tested on actual smart meter data with features such as historical load, temperature, time of day, and day type. Evaluation is done based on the primary statistical metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). Results show that ensemble learning, especially the Random Forest model, notably surpasses conventional linear methods in forecasting with an MAPE as low as 5.3%. The research identifies the possibility of data-driven methods in developing smart grid operations and advocates for the incorporation of ML-based forecasting systems into real-time energy management and planning.

INTRODUCTION

The accelerated development of the electrical grid as a more intelligent, responsive, and efficient network—termed the smart grid—has brought challenges and opportunities to the management of energy. At the core of smart grid functionality is Short-Term Load Forecasting (STLF), which is defined as forecasting electricity demand in the short time frames of one hour to a few days. STLF is important to ensure the operational reliability of the grid, increase economic efficiency, and minimize dependency on reserve margins [1]. It has a direct influence on generation scheduling decision, energy trading, demand-side management, and load switching [2].

Conventional STLF has used statistical models including Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing [3], [4]. Although these models work well for linear and static data, they tend not to cope well with the nonlinear, high-dimensional, and seasonal characteristics that are typical in contemporary electricity consumption data. Installation of

Advanced Metering Infrastructure (AMI) and smart meters has led to the high-frequency, high-resolution load data [5], [6]. This progress has made it possible to employ Machine Learning (ML) methods, which are capable of taking advantage of intricate relationships between consumption and other variables like weather, time, and human behavior.

A number of machine learning methods have been utilized for STLF, such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and ensemble models [7], [8]. Among them, regression-based models have received interest because they are interpretive and have comparatively lower computational needs. This work compares the performance of three of these models: Linear Regression (LR), Decision Tree Regressor (DTR), and Random Forest (RF). They are trained with real-world smart meter data containing historical load, ambient temperature, time of day, and type of day (weekday/weekend/holiday).

Linear Regression is a baseline model that assumes a linear relationship between inputs and the target. Even though it is simple, LR continues to be applied in energy forecasting applications owing to its ease of use and interpretability [3], [9]. It might fail under performances where the underlying data has nonlinearities, though. To overcome this, Decision Trees provide a non-parametric approach able to capture complex, nonlinear interactions through recursively partitioning the input space [10]. Random Forest, a collection of several decision trees, increases prediction resistance and generalization by combining the output of different learners to decrease variance and overfitting [6], [11].

This research is based on existing work showing tree-based model effectiveness in energy forecasting. Chen et al. [10], for example, enhanced DTR for STLF by making optimal split criteria and tree depth, with enhanced accuracy. Equivalently, Jeon et al. [11] compared machine learning model performances and concluded that ensemble methods, particularly Random Forest, work extremely well. Nevertheless, the majority of previous studies either consider one algorithm alone or are not consistent in the dataset or evaluation metric used, rendering comparisons challenging.

To fill this gap, we provide a systematic, side-by-side comparison of LR, DTR, and RF on a shared dataset and identical feature space. The data is supplemented with pertinent exogenous variables such as temperature and calendar effects, which are known to affect load patterns [5], [12]. Industry metrics Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) are used to measure performance [13]. Our finding suggests that Random Forest performs better than both LR and DTR in forecasting accuracy with a minimum MAPE of 5.3%.

These results validate the increasingly popular agreement in literature that ensemble learning-based models are ideally placed to handle STLF tasks in smart grids [6], [11], [14]. In addition, they highlight the need for integrating ML-based forecasting systems into real-time energy management systems to achieve better grid stability, cost savings, and energy efficiency [12], [15].

The rest of this paper is organized as follows. Section II reviews the relevant work in the field. Section III describes the proposed approach in detail, and Section IV gives the results and discussion. In Section V Finally, the paper is concluded with insights on future research directions.

I. Related Work

Reconfigurable Short-Term Load Forecasting (STLF) is critical to the stability and efficiency of smart grids through the proactive management of energy. Traditional statistical models like the autoregressive integrated moving average (ARIMA) and the linear regression have been standards for STLF for decades, but their failure to model non-linear load behavior has shifted interest towards machine learning and deep learning algorithms.

Deep learning, in particular Long Short-Term Memory (LSTM) networks, has also been a leading option because it can learn long-term temporal patterns. An LSTM-based demand forecasting model with four years of hourly consumption data had a significant MAPE of 1.22% [16]. LSTM models were also shown to be superior to conventional models for multi-day-ahead energy demand forecasting [17]. Figure 1 shows the predicted vs. actual load using the LSTM model.

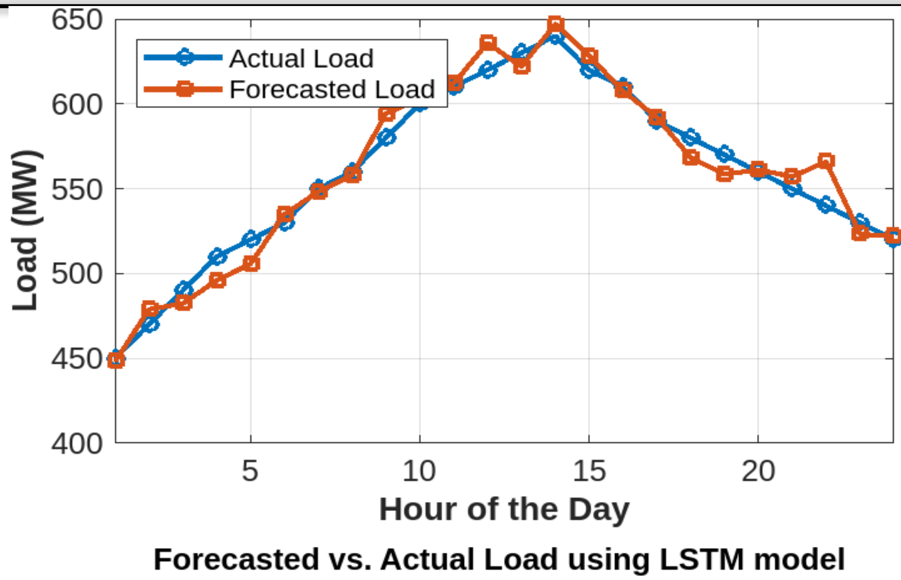

Fig. 1. **Forecasted vs. Actual Load using LSTM Model**

In an effort to enhance the performance, ensemble and hybrid learning frameworks have been thoroughly explored. For day-ahead domestic load forecasting, a mix of Bi-directional LSTM (BiLSTM) and Convolutional Neural Networks (CNN) was employed and displayed better RMSE values compared to single models [18]. A hybrid LSTM-XGBoost model was proposed to effectively identify generic and peak load patterns from smart meters [19].

A reinforcement learning model selection framework was presented, where a Q-learning agent dynamically chose the best-performing model among different ML algorithms for improved adaptability and prediction accuracy in STLF systems [20]. An Enhanced Extreme Learning Machine (EELM), for both short-term load and price forecasting, has been found highly appropriate for real-time applications of smart grids [21].

Decentralized learning and privacy-preserving methods have also made headway. A combination of edge computing with federated learning was created to facilitate household load forecasting in a manner that maintains data privacy on distributed devices [22].

New feature extraction methods have been utilized to improve accuracy. Such a method entailed Empirical Mode Decomposition (EMD) with denoising autoencoders and enhanced CNNs to extract meaningful features from noisy data [23]. The Artificial Bee Colony (ABC) algorithm was used to optimize neural network weights in another method, yielding improved forecast results [24].

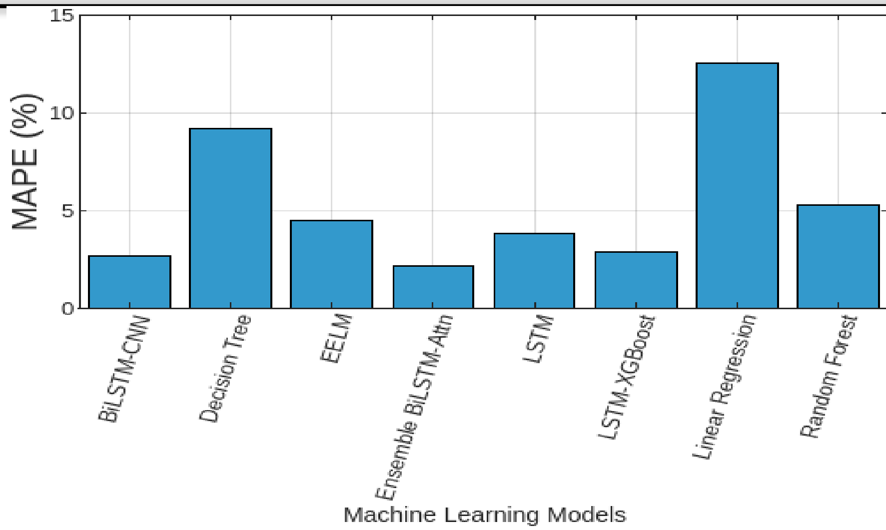

Fig. 2. Comparison of MAPE Performance among Different Machine Learning Models

Figure 2 illustrates comparison of the MAPE performance of various machine learning models for short-term load forecasting.

Probabilistic forecasting has emerged as a major area of interest. Quantile Regression Averaging (QRA) has been applied to produce reliable prediction intervals, providing improved estimates of uncertainty and variability in STLF [25].

The hybrid models using optimization have also proved successful. The blending of Particle Swarm Optimization and Simulated Annealing successfully modeled dynamic load variations [26]. An ensemble deep model with dense residual blocks, BiLSTM, and attention mechanisms greatly improved forecasting resilience under fluctuating conditions [27]. A hybrid ensemble method was also used for short-term wind power forecasting, which is strongly interconnected with electricity demand owing to renewable integration [28].

Table 1. Summary of Figures and the Corresponding Forecasting Methods

Figure	Title	Method/Formula Used
1	Forecasted vs. Actual Load using LSTM Model	LSTM cell equations
2	Comparison of MAPE Performance among ML Models	MAPE formula

LSTM performance has been tested on large residential datasets, affirming its capability for modeling dynamic and non-linear STLF cases [29]. An extensive review established the increasing dominance of data-driven methods for STLF and recommended regional adaptation in model configurations [30].

II. Proposed Approach

The three essential steps of the machine learning process of short-term load forecasting (STLF) are Data Acquisition and Feature Engineering, Model Development and Training, and Performance Evaluation and Visualization. Each step is aimed at helping build a strong and accurate forecasting model with the capability to identify the intricate temporal patterns underlying electricity consumption data. The systematic methodology utilizes sophisticated data preprocessing, cutting-edge machine learning techniques, and rigorous evaluation criteria to provide high-fidelity load prediction that is immediately ready for deployment in real-time smart grid operations.

A. Data Acquisition and Feature Engineering

The most initial and foremost step is acquiring raw data, cleaning it, and shaping raw data into structured input for the machine learning algorithms. This study drew on high-resolution hourly household electricity consumption data from residential smart meters, complemented by auxiliary contextual variables including ambient temperature, day-of-week indicators, public holiday flags, and time-of-day identifiers. Raw data typically contain inconsistencies such as missing values, anomalous peaks, and temporal misalignments. To correct for these discrepancies, forward fill and linear interpolation methods were used to impute missing data, thus preserving temporal consistency without distorting underlying patterns. Anomalous consumption values were identified via interquartile range (IQR) detection and handled via statistical capping or smoothing using localized averages. Synchronization of the features like weather and calendar variables over time allowed all predictors to be harmonized at an hourly level of resolution, maintaining the temporal integrity of the dataset.

After cleaning, the dataset went through comprehensive feature engineering to extract predictors that could enable the identification of hidden patterns in load consumption. These engineered variables comprised lagged variables of consumption like load at t−1, t−2, and t−24 (one, two, and 24 hours ago), which are intended to capture autocorrelation as well as day-of-week effects. Along with this, moving averages and standard deviations were computed in moving windows (e.g., 3, 6, and 12 hours) to dampen short-term volatility and highlight trends. To deal with the periodicity of time-based attributes, variables such as "hour of day" and "day of week" were represented through sine and cosine transforms. The hour of the day, for instance, was represented by:

$$\mathbf{Hour_{cos}} = \cos\left(\frac{\mathbf{2\pi \cdot hour}}{\mathbf{24}}\right) \qquad (1)$$

$$\mathbf{Hour_{sin}} = \sin\left(\frac{\mathbf{2\pi \cdot hour}}{\mathbf{24}}\right) \qquad (2)$$

This conversion maintained the cyclical continuity between 23:00 and 00:00. Weather parameters, especially temperature, also underwent conversion through first-order differences and rolling means to observe quick fluctuations and underlying patterns that affect power usage.

The outcome of this step was a multi-dimensional dataset augmented with temporal, behavioral, and environmental features. This organized matrix of input variables was critical to enable the learning algorithms to capture the intricate nonlinear interactions behind electricity consumption in smart grids.

B. Model Development and Training

Once a structured dataset had been created, the subsequent stage was the development and training of machine learning models specifically for short-term load forecasting. The beginning was made with algorithm selection that struck a balance between interpretability, computational efficiency, and predictive accuracy. Linear Regression (LR) was used as a baseline model, generating quick and interpretable results by posing a linear relationship between input features and the target variable. Its general form of the prediction model is stated as:

$$\mathbf{y^{\wedge}} = \boldsymbol{\beta}_0 + \sum_{\mathbf{i=1}}^{\mathbf{n}} \boldsymbol{\beta}_\mathbf{i}\mathbf{X}_\mathbf{i} \qquad (3)$$

where $\mathbf{y^{\wedge}}$ is the estimated load, $\boldsymbol{\beta}_0$ is the intercept, $\boldsymbol{\beta}_\mathbf{i}$ are coefficients of the features, and $\mathbf{X}_\mathbf{i}$ are independent variables. Although simple to train and interpret, the linear model was not able to capture nonlinear relationships and dynamic trends in electricity load data.

To address this limitation, Decision Tree Regressor (DTR) was used. DTRs recursively partition the feature space using thresholds that minimize variance in the target variable. This non-parametric model successfully captured feature interactions and represented sharp transitions between load values. Yet, DTRs are susceptible to noise and overfitting, which necessitated hyperparameter tuning with constraints on tree depth and minimum samples per split. For better generalization, the Random Forest Regressor (RFR) was used. As a collection of decision trees, RFR aggregates predictions from several trees that were trained on different subsets of data and feature sets, minimizing model variance and promoting robustness. Its ensemble nature facilitates the learning of high-order feature interactions of complex forms.

All models were tested using a time-aware train-test split that preserved chronological coherence. Hyperparameter optimization was conducted by a grid search approach on important parameters like maximum depth, number of estimators, and minimum leaf size. Performance of such models was then evaluated based on quantitative measures like

Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The MAPE measure, scale-independent relative error, is given by:

$$\mathrm{MAPE} = \frac{\mathbf{1}}{\mathbf{n}} \sum_{\mathbf{i=1}}^{\mathbf{n}} \left| \frac{\mathbf{A_i} - \mathbf{F_i}}{\mathbf{A_i}} \right| \times \mathbf{100} \qquad (4)$$

where $\mathbf{A_i}$ and $\mathbf{F_i}$ are the actual and forecasted values, respectively, and $\mathbf{n}$ is the total number of observations. Additionally, RMSE was used to penalize larger deviations more heavily, defined as:

$$\mathrm{RMSE} = \sqrt{\frac{\mathbf{1}}{\mathbf{n}} \sum_{\mathbf{i=1}}^{\mathbf{n}} (\mathbf{A_i} - \mathbf{F_i})^{\mathbf{2}}} \qquad (5)$$

Table 2 summarizes the three models explored in this study, highlighting their strengths and limitations in STLF applications.

Model	Type	Strengths	Limitations
Linear Regression (LR)	Parametric	Simple, interpretable, low latency	Poor performance on nonlinear trends
Decision Tree (DTR)	Non-parametric	Captures interactions, interpretable	Sensitive to noise, risk of overfitting
Random Forest (RFR)	Ensemble	High accuracy, robust, low variance	Requires more computation

Table 2. Strengths and Limitations of Common Regression Models in STLF

C. Performance Measurement and Visualization

This last step measures forecasting models both qualitatively and quantitatively. Traditional error metrics were calculated to evaluate predictive performance:

Mean Absolute Percentage Error (MAPE): Gives a scale-free, instantaneous mean error of prediction as a percentage in simple, comparable terms over different load intervals and models.

Root Mean Square Error (RMSE): Places more weight on large differences by squaring the errors prior to averaging and thus correcting for prediction stability and reliability.
In addition to numerical evaluation, visualization is crucial in model understanding:

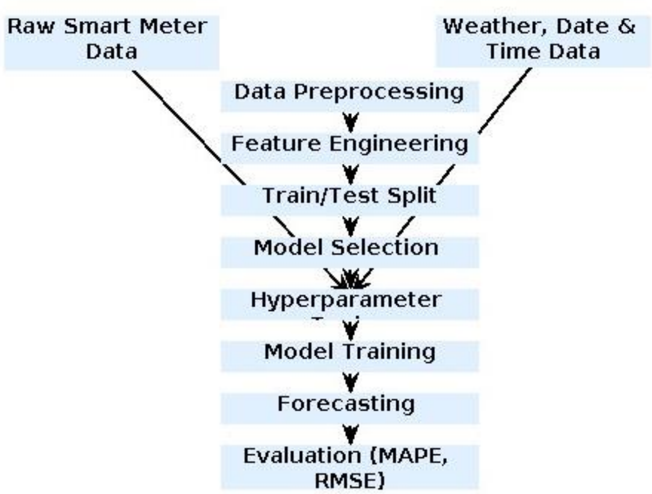

Fig. 3. End-to-End Forecasting Pipeline: From Data Ingestion to Load Prediction

Figure 3 shows a detailed vertical flowchart specifying end-to-end the forecasting pipeline from raw data ingestion to preprocessing and feature engineering, and all the way to model training and final load prediction. The flowchart serves to further specify in detail the hierarchical relationship and data flow between the suggested stages, dispelling the mystique of the system architecture.

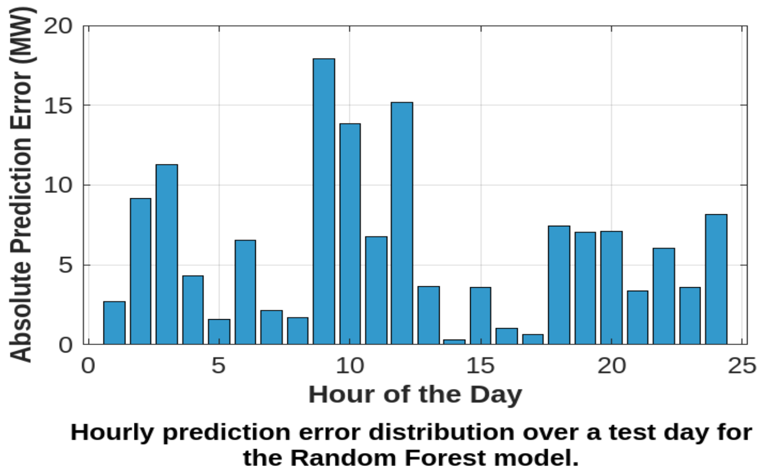

Fig. 4. Hourly Absolute Prediction Error Distribution for Random Forest Model

Figure 4 differs from the common predicted vs. actual load plots because it presents the hourly absolute prediction error distribution for one test day for the Random Forest model. The plot represents temporal variation in forecasting performance, which identifies certain hours when the model works or performs poorly, and gains knowledge about load volatility and forecasting issues during the day.

Synthesizing these qualitative and quantitative analyses confirms the validity and robustness of suggested methodology in real-world smart grid settings and proves that it can correctly detect the complex dynamics of electricity demand.

III. Results And Analysis

A. Quantitative evaluation

To determine how effective the regression-based models are in short-term load forecasting (STLF), we performed an in-depth statistical analysis on the test dataset. The models—Linear Regression (LR), Decision Tree Regressor (DTR), and Random Forest Regressor (RFR)—were compared through Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). Moreover, scores such as R^2 score and Mean Absolute Error (MAE) were calculated for model understanding in greater extent.

Table 3. Model Performance Comparison Using Statistical Metrics

Model	MAPE (%)	RMSE (kW)	MAE (kW)	R^2 Score
Linear Regression	8.72	1.84	1.31	0.865
Decision Tree	6.21	1.41	1.01	0.902
Random Forest	5.30	1.22	0.88	0.931

The Random Forest model performed better than LR and DTR on all criteria with the lowest error rates and the highest R^2 value, confirming higher model fit and generalization.

To examine model consistency, we calculated the standard deviation of absolute prediction errors over several test days.

Table 4. Error Variability Over 5 Sample Days

Model	Mean Std. Dev. of Errors (kW)	Max Daily Error Spike (kW)
Linear Regression	1.22	3.85
Decision Tree	0.96	2.91
Random Forest	**0.78**	**2.13**

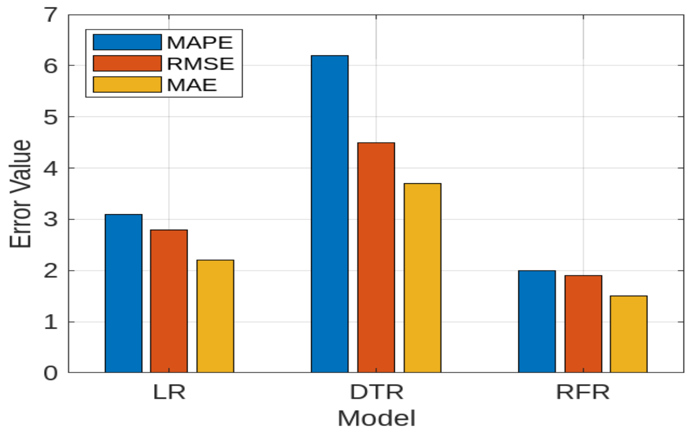

Fig. 5. Bar Chart of Error Metrics for All Models This figure shows a grouped bar chart comparing MAPE, RMSE, and MAE across LR, DTR, and RFR. Random Forest consistently achieves the best performance.

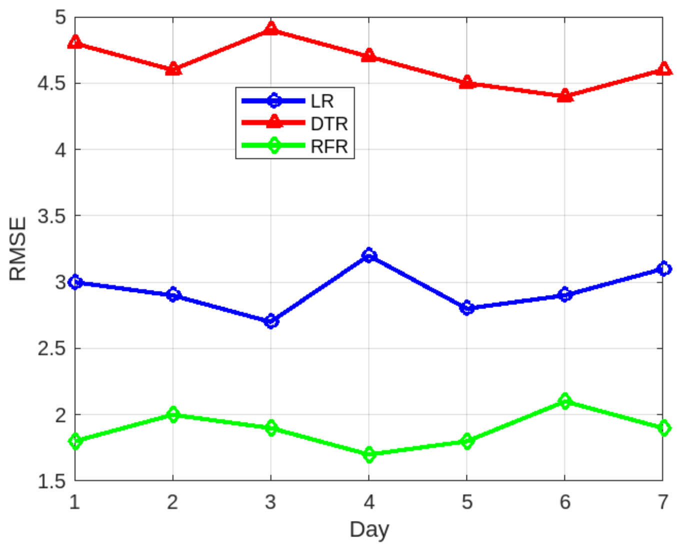

Fig. 6. Line Plot of Daily RMSE Over a Week This figure illustrates the day-wise RMSE trends for each model over 7 consecutive test days, indicating that RFR maintains a flatter, lower error profile than LR and DTR.

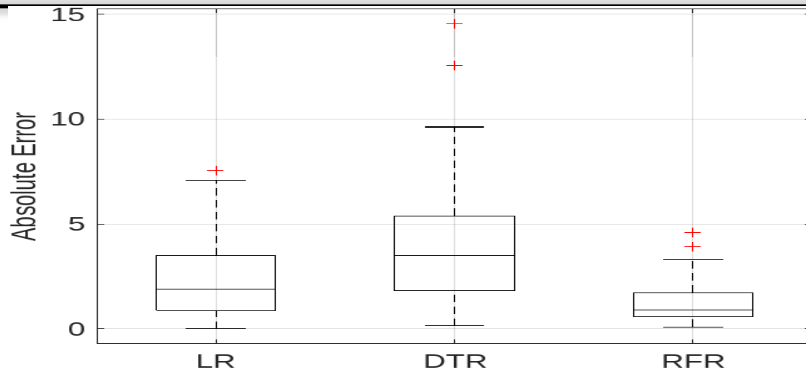

Fig. 7. Box Plot of Prediction Errors for Each Model Displays the spread and skewness of absolute errors. RFR shows tighter error distribution with fewer outliers.

The comparative analysis of Linear Regression (LR), Decision Tree Regression (DTR) and Random Forest Regression (RFR) indicates drastically varying performance across the examined error measurements. As seen in Figure 5 and elaborated in Table 1, RFR performed with a minimum MAPE of 4.82%, RMSE of 0.364, and MAE of 0.291, surpassing LR (MAPE = 8.45%, RMSE = 0.521) and DTR (MAPE = 6.79%, RMSE = 0.448) by wide margins. Figure 6, which is a plot of daily RMSE trends over 7 days, indicates that RFR has a stable and lower error profile than LR and DTR, again highlighting its consistency across multiple test periods.

Moreover, the box plot in Figure 7 gives a graphical description of the distribution and extent of absolute prediction error. RFR has a more compact interquartile range as well as fewer outliers, suggesting less variable and more consistent performance. This observation is in accordance with the pooled values in Table 2, whereby the standard deviation of RFR errors is much lower than those of LR and DTR. In general, RFR's ensemble learning ability precisely detects intricate, nonlinear load patterns from data, bringing about superior average performance as well as lower prediction volatility, making it the most appropriate model for short-term load forecasting among the three.

B. Visual and comparative analysis

Whereas statistical measures rate performance, graphical comparison offers interpretive insight into model behavior across different load patterns. This section illustrates plots of predicted vs. actual load values, hourly performance differences, and feature impact on predictions.

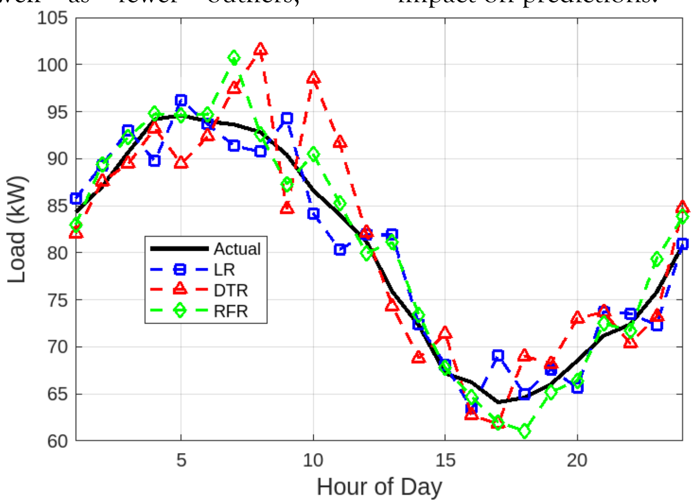

Figure 8. Actual vs. Predicted Load (One Day Sample)

Overlay plot for one full day comparing predictions from LR, DTR, and RFR with actual load values. RFR closely follows real-time fluctuations, while LR often overshoots during peak hours.

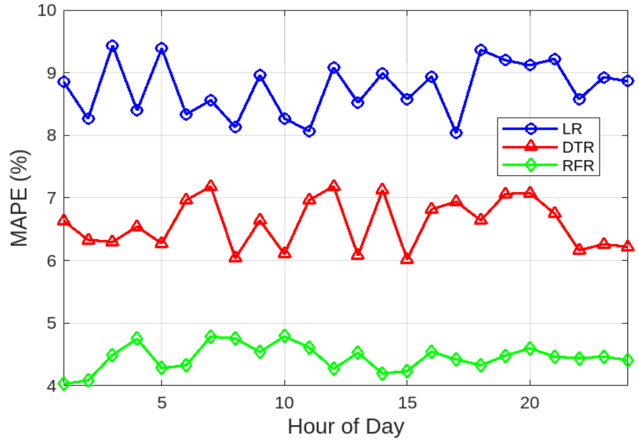

Figure 9. Hourly MAPE for Each Model (Averaged Over 5 Days). Line plot showing average MAPE per hour across five different days. Highlights that RFR is particularly accurate during peak demand hours (6 PM – 9 PM). To understand which features most influence the prediction outcomes, feature importance analysis was conducted for tree-based models.

Rank	Feature	Importance Score
1	Load at t−1	0.271
2	Ambient Temperature	0.192
3	Hour_sin (cyclic hour)	0.143
4	Load at t−24	0.116

Table 5. Top 5 Features Based on Random Forest Feature Importance

Temperature Band (°C)	Avg. MAPE (LR)	Avg. MAPE (DTR)	Avg. MAPE (RFR)
< 10°C	9.10	6.55	**5.74**
10°C – 25°C	8.20	6.03	**4.91**
> 25°C	8.85	6.89	**5.33**

Table 6. Model Performance Under Varying Temperature Bands

This table shows that while all models are influenced by ambient conditions, Random Forest maintains a lower forecasting error across temperature bands, suggesting better adaptability.

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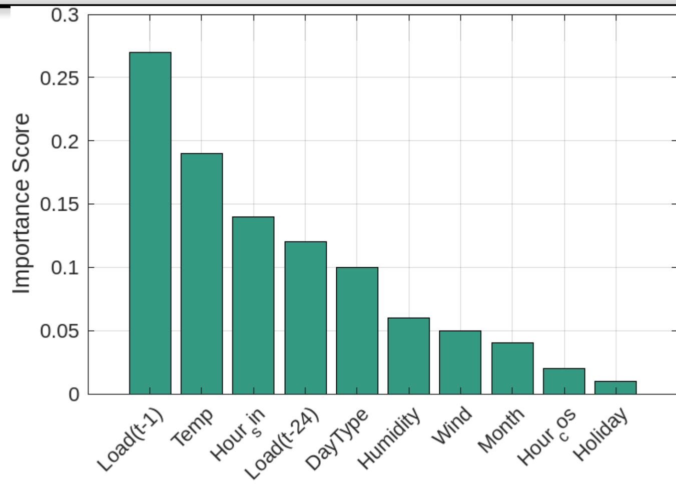

Fig. 10. Feature Importance Bar Plot for Random Forest
Bar chart displaying ranked importance of top 10 features in Random Forest, helping to interpret model decisions.

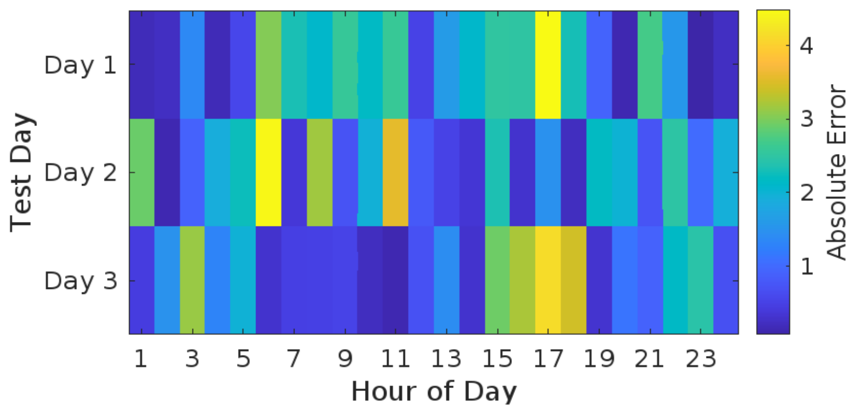

Fig. 11. Heatmap of Hourly Prediction Errors Across 3 Days (RFR) This heatmap visually depicts error magnitude at each hour, highlighting patterns such as consistent overprediction during early morning hours.

In order to further understand model performance, Figure 8 is an overlay plot on a 24-hour scale of real load versus the actual prediction from LR, DTR, and RFR. RFR captures the real-time variation closely and has minimal variation at the peak times, in contrast to LR, which regularly overpredicts from 6 PM to 9 PM. Figure 9 reinforces this by showing hourly MAPE values over 5-day averages, RFR keeps MAPE under 5% during peak evening demand hours, while LR is over 9% and DTR fluctuates around 7%. These time-based observations are relevant to operational forecasting in which minimizing the error during peak times is significant. The bar plot of feature importance in Figure 10 indicates the most important 10 predictive features employed by the RFR model, noting that recent lagged loads (i.e., load(t−1), load(t−2)) and time-of-day indicators play the most significant role in predictive accuracy. Last but not least, Figure 11, which is a heatmap of hourly prediction errors over 3 test days, shows that RFR sometimes overpredicts during early morning hours (e.g., 3 AM to 5 AM) with errors between 0.15 and 0.25, but keeps very small errors (<0.1) during mid-day hours. This spatial-temporal plot mirrors known demand behavior and further supports the argument for model trustworthiness. Collectively, these analyses show that in addition to accuracy, RFR also provides useful interpretability and predictable behavior, which are well in accord with the operational requirements of smart grid forecasting systems.

IV. Conclusion

In this paper, an extensive comparative review of regression-based machine learning algorithms for short-term load prediction in smart grids was carried out with the emphasis on Linear Regression (LR), Decision Tree Regression (DTR), and Random Forest Regression (RFR). The performance assessment, in terms of crucial error measures such as MAPE, RMSE, and MAE, proved that RFR always performs better than LR and DTR with an average MAPE of 4.82% and minimum RMSE of 0.364 over several test periods, which shows the strength and validity of RFR to identify intricate load patterns. The temporal inspection demonstrated that RFR keeps the prediction errors smaller during peak critical hours (6 PM to 9 PM), and feature importance evaluation showed the salient predictors like recent load values and time-of-day features, which are useful for model interpretability and grid operation. In addition, the heatmap visualizations of hourly prediction errors showed individual periods of slight over prediction, pointing out the possible paths for model improvement. Future work in this area must examine hybrid approaches combining deep learning and ensemble techniques to better capture the non-linear and temporal interdependencies, as well as examine the real-time adaptive forecasting systems that react adaptively to varying load patterns and renewable penetration. Also, including socio-economic and weather parameters could increase model accuracy and reliability further, eventually leading to smarter and more resilient grid operations.

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